Multi-channel microseismic signals classification with convolutional neural networks

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ABSTRACT

Identifying and classifying microseismic signals is essential to warn of mines' dangers. Deep learning has replaced traditional methods, but labor-intensive manual identification and varying deep learning outcomes pose challenges. This paper proposes a transfer learning-based convolutional neural network (CNN) method called microseismic signals-convolutional neural network (MS-CNN) to automatically recognize and classify microseismic events and blasts. The model was instructed on a limited sample of data to obtain an optimal weight model for microseismic waveform recognition and classification. A comparative analysis was performed with an existing CNN model and classical image classification models such as AlexNet, GoogLeNet, and ResNet50. The outcomes demonstrate that the MS-CNN model achieved the best recognition and classification effect (99.6% accuracy) in the shortest time (0.31 s to identify 277 images in the test set). Thus, the MS-CNN model can efficiently recognize and classify microseismic events and blasts in practical engineering applications, improving the recognition timeliness of microseismic signals and further enhancing the accuracy of event classification.

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1. INTRODUCTION

Microseismic monitoring technology (MMT) has found extensive applications in underground engineering for disasters and safety monitoring [1]. Specifically, it has been utilized for location monitoring [2], [3], as well as forecasting and providing early warning systems for rock bursts [4], and mine earthquake disasters during mining operations [5], [6]. The basic principle involves identifying microseismic events by analyzing prominent features within the monitoring data [7]. Subsequently, the relevant parameters of these events are analyzed to facilitate informed decision-making [8]. Due to the complex geological environment of mines [9], many interference signals frequently mix with the recorded microseismic signals, such as blasting, rock drilling, fan vibration, and other noises generated during engineering operations [10]. Therefore, the basis of MMT is to identify microseismic events quickly and accurately, which determines the timeliness and effectiveness of mine safety early warning [11].

Earlier studies have investigated several strategies, such as conventional signal processing methods and machine learning algorithms [12], [13], to identify and classify microseismic signals [14]. However, these techniques have limitations regarding their efficiency and accuracy. Recently, convolutional neural networks (CNNs) [15], [16] have shown great promise in identifying and categorizing images. Based on this

success, some researchers employed CNNs to successfully recognize and categorize microseismic signals [17]. However, these studies have primarily focused on single-channel signals, and further research is necessary to explore the application of CNNs to multichannel signals. The higher dimensionality of multichannel signals presents unique challenges, and the effectiveness of CNNs for these signals is an active research area.

Traditional methods for identifying microseismic events and blasts primarily rely on manual or engineering experience, which often results in significant and parameter analysis errors as well as time delays. Extensive research has been conducted by experts and scholars in the field of recognition and classification, as evidenced by previous studies [18], [19]. Traditional methods typically rely on statistical analysis of waveform characteristics to classify microseismic events and blasts. However, these methods often require manual experience for selecting characteristic parameters, resulting in limited generalizability and robustness due to their specific applicability to certain cases or mines. For example, researchers conducted an analysis on the characteristic patterns of source parameters associated with microseismic events and blasts [20], [21]. They developed a statistical model for the automatic identification of such events, taking into account the probability density distribution of each parameter and its impact on identification accuracy. However, the recognition effect of this method on different mine data samples is quite different, and the robustness is not high.

With the explosive growth of data, the use of machine learning for image classification has become popular [22], [23]. Deep learning [24]–[26] is a widely used method at present, which automatically extracts features through data-driven, and obtains the specific feature representation of the dataset based on the learning and training of many samples. It is more efficient and accurate in the expression of data sets without manual intervention. Lin *et al.* and Lin *et al.* [27], [28] have proposed two methods, deep convolutional neural network and spatial pyramidal pool (DCNN-SPP) and DCNN and support vector machine (DCNN-SVM), to automatically identify and classify multi-channel microseismic waveforms, with accuracy improved from 91.13% to 98.18%. Li *et al.* [10] introduced a deep learning method for microseismic waveform classification based on computer vision, which analyzed both the waveform of the microseismic signal and the corresponding spectrogram of the waveform. Four deep learning models were used for experiments, including VGG-16 [29], ResNet18 [30], AlexNet [31], and their ensemble models. The results showed that these models perform well in recognizing the features of waveform graphs and can accurately predict data categories, among which the ensemble model had the highest recognition accuracy of 98%. The end-to-end automatic classification of the original waveform was realized, and it proved that the identification effect of the original waveform and the spectrogram was basically the same.

This study proposes a CNN-based model named microseismic signals convolutional neural network (MS-CNN) to enhance the precision and effectiveness of microseismic event recognition and classification. This study's goal is to assess how well CNNs and related transfer learning models work. The researchers [32], [33] in accurately classifying microseismic events and blasts in mines. We developed and trained multiple deep learning models, comprising three conventional models (AlexNet, GoogLeNet, and ResNet50) and one CNN model to accomplish this. We assessed the classification performance of these models using five metrics based on an identical dataset. After analyzing the experimental results, we pinpointed the most effective model for this purpose, hoping that this research will assist users in making informed decisions.

2. METHOD

The application of CNNs for microseismic waveform recognition and classification is guided by several fundamental principles. These include the capacity of deep learning algorithms to extract intricate features from multi-channel data, the utilization of supervised learning to train the model, and the iterative optimization of the model's parameters to minimize classification error. The CNN model is trained using labeled data, where the model's parameters and weights are adjusted to minimize classification error. This optimization process often involves iterative algorithms like stochastic gradient descent, which update the model's parameters based on the discrepancy between expected and actual labels. Convolutional layers play a crucial role in this process by applying filters to the input data to extract local features [34]. Additionally, pooling layers are utilized to down-sample the feature maps, simplifying the computational complexity of the model. Once trained, the CNN can classify new and unseen data by inputting it into the network and leveraging the learned parameters to predict the type of microseismic event present in each segment.

2.1. Microseismic signals convolutional neural network

Figure 1 depicts the MS-CNN model's hierarchical structure, which comprises an input layer, two convolutional layers, a pooling layer, two fully connected layers, and an output layer. It abstracts the image into data layer by layer to provide the necessary feature representation, and then maps the features to the task objective. Humans do not need to intervene in the feature selection process during CNN training. The neural network automatically learns image local features through convolution and backpropagates the error through the loss function to obtain the optimal convolution coefficients (weights and biases). The identification

and classification principle of the MS-CNN model was mainly composed of two parts, one part featured learning (convolution, activation function, and pooling layers), and the other part was classification (full connection layer).

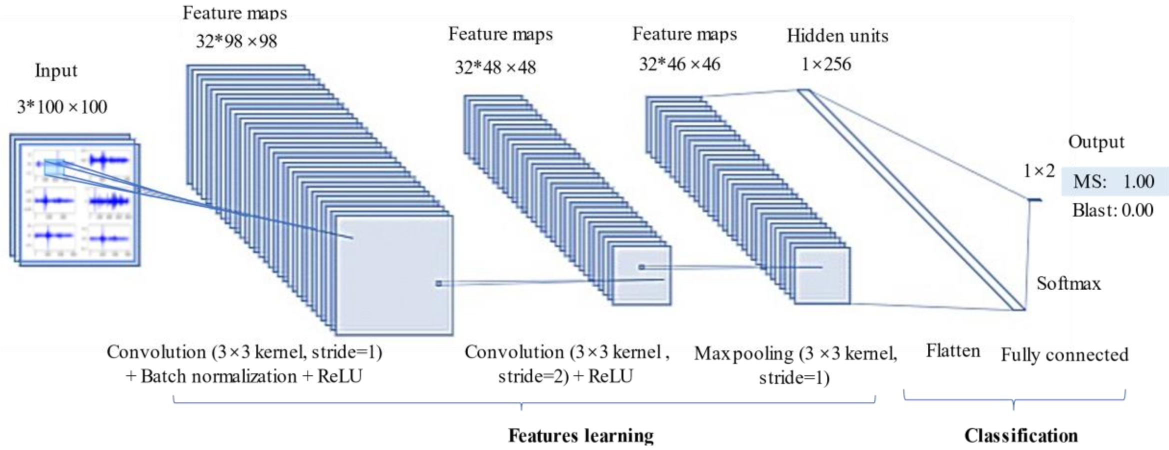

Figure 1. Structure of MS-CNN, a multichannel microseismic waveform recognition and classification model

2.1.1. Feature extraction

The convolutional and pooling layers are crucial to CNN's capacity to automatically extract image features. The weight and bias parameters in the convolution operation are effectively solved during the CNN learning process utilizing the dataset and loss function [35]. The value of the feature map is determined using (1), where x represents the input image, f denotes the convolution kernel, and m, n represent the row and column indices, respectively, of the calculation result [36].

$$D[m,n] = (x * f)[m,n] = \sum_i \sum_j f[i,j]x[m-i,n-j] \quad (1)$$

The pooling layer, also known as the downsampling layer, reduces the dimension of the feature map by pooling each feature map, thus reducing the number of parameters in CNN, and avoiding overfitting [37]. The window size of the pooling operation can be specified as any size. There are two main pooling operations: max pooling and average pooling. The MS-CNN model used max pooling. The maximum pooling function uses the maximum value in the small block as the feature output of the block. When the image undergoes small changes such as translation, scaling, and rotation, it is still possible to obtain the maximum value at the same position, which is the same as the response before the change, thus realizing the spatial invariance feature.

2.1.2. Classification

The classification of the MS-CNN was achieved by fully connected layers. Since MS-CNN was a supervised learning, the model was trained based on the labeled training samples to obtain the weights of the fully connected layer. When using the model for outcome recognition, the weights obtained from the training of the model and the results calculated from the deep network after the previous convolution, activation function, and pooling, were weighted and summed to obtain the predicted value of each outcome. Then the maximum value was taken as the result of the recognition. As shown in Figure 1, the probability of a microseismic event was finally calculated to be 1.00, and the probability of a blasting event was 0.00. Therefore, the event corresponding to this figure was finally determined to be a microseismic event.

The output layer of the model computes the error using the cross-entropy loss function, which assesses the similarity between the predicted output and the desired output. In the back-propagation process, this information is then used to optimize or update the parameters of each layer. In (2) [38] represents the mathematical expression for the cross-entropy loss function. Where N represents the sample size, K denotes the number of categories, and $t_{ij}=1$ if sample i belongs to the jth category, otherwise $t_{ij}=0$. The variable y_{ij} represents the probability that sample i belongs to the jth category.

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{K} t_{ij} ln y_{ij} \quad (2)$$

The main advantages of MS-CNN are its ability to handle multichannel data. In microseismic applications, multiple sensors are often used to record microseismic waves, and MS-CNN can use all the available channels to improve the accuracy of the recognition and classification task. MS-CNN is trained using a dataset of microseismic event waveforms with labeled classes. The model learns to recognize patterns in the data and associate them with specific classes. Once trained, MS-CNN can be used to classify new microseismic waveforms based on their features and similarities to the learned patterns.

2.2. Model construction

Figure 1 shows the parameter settings of each layer for the MS-CNN model, and the number of learning parameters is shown in Table 1. Before the image was fed into the model, the color image was preprocessed by transforming its size from 432×288 pixels to 100×100 pixels. After the image (e.g., X_0) is inputted into the model, first, the Input layer would be normalized to X_0 (size width*height*channels=100×100×3). The $C1$ layer used a (3×3) convolution kernel to perform 32 convolutions on the X_0 to form a (32×98×98) tensor. Then the $C2$ layer continued to use the (3×3) convolution kernel to perform 32 convolutions on the output data of the $C1$ layer, and finally obtained a (32×48×48) structure tensor. In the $C1$ and $C2$ layers, the stride is (1×1) and (2×2), respectively. To facilitate feature extraction and reduce the amount of computation, a pooling operation was performed on the output data after the $C2$ layer by pooling a maximum of (3×3) $P1$ to form a pooling tensor of (32×46×46). After pooling, a fully connected layer was added to flatten the $P1$ data into a one-dimensional vector, and the number of output neurons in the $Fc1$ was set to 256. Finally, the output size of the $Fc2$ is 2, and the softmax function was added after $Fc2$ to calculate the probability value of each waveform belonging to each category. After obtaining the probability values of the two categories, the category corresponding to the maximum probability value was selected as the output value in the output layer. The activation functions of MS-CNN all used ReLU (rectified linear unit), which existed between $C1$ and $C2$, and between $C2$ and $P1$, respectively. Additionally, to hasten CNN's training and lessen the sensitivity of the initialization of the network, we added a batch normalization layer between the $C1$ and the ReLU layer. Mini-batch processing of all observations for each channel was implemented at this layer. And adopted the dropout method to alleviate overfitting.

Table 1. Learning params numbers for the layers of the MS-CNN model

Layer type	Learnable	Params
Convolution layer $C1$	Weights (3×3×3×32); Bias (1×1×32)	896
Batch normalization layer	Offset (1×1×32); Scale (1×1×32)	64
Convolution layer $C2$	Weights (3×3×32×32); Bias (1×1×32)	9248
Max pooling layer $P1$	–	0
Fully Connected layer $Fc1$	Weights (256×80000); Bias (256×1)	20480256
Fully Connected layer $Fc2$	Weights (2×256); Bias (2×1)	514

3. RESULTS AND ANALYSIS

To comprehensively evaluate the performance of CNN models, we conducted experimental tests using existing field data. The training process and test results of the MS-CNN model were longitudinally analyzed and compared to CNN [1], AlexNet, GoogLeNet, and ResNet50 models. Our research findings demonstrate that the MS-CNN model surpassed other models in terms of accuracy and computational efficiency. This was observed by achieving both high classification accuracy and low training time. These results suggest that the MS-CNN model has significant potential for use in real-world applications.

3.1. Data

To proper data preparation is essential for the successful recognition and classification of multi-channel microseismic waveforms using CNN-based models. Careful attention should be paid to data collection, preprocessing, labeling, and splitting to ensure that the CNN is trained and tested on high-quality data. Real-time data from a mine microseismic monitoring system in China's Shanxi province was used in this study. A 26-channel microseismic monitoring system was installed by the engineers based on the mine's geological setting and mining strategy. Due to the large volume of data and the similarity among each type of event, data from March 29 to April 19, 2022, were selected for this study. This was a total of 22 days of data and a database size of 6.85 GB, chosen for computational performance reasons.

Firstly, we filtered all event data from the database with at least 6 triggered sensors. Then, we used the Python plotting library Matplotlib to draw a 2D waveform graph of the event based on the sample time magnitude data, which was saved as an event waveform with six subplots as input. Next, we manually screened and marked the noise events, such as rock drilling and mechanical vibration, to filter them out. Finally, we obtained the multi-channel waveform of two types of typical blasts and microseismic events. Examples of

waveforms for a microseismic event are shown in Figure 2(a), and those for a blast event can be seen in Figure 2(b). The vertical axis shows the signal amplitude, and the horizontal axis depicts a time in microseconds. The experimental sample contained a total of 1386 images, including 512 waveform images of microseismic events and 874 waveform images of blasts.

The classification performance of various models using the same dataset will be compared and examined, control variables were employed to ensure fair training and testing. The distribution of sample sizes for each event type in the dataset is presented in Table 2. The dataset was split into two chronological sections: the first 80% were used as the training set, while the final 20% were utilized as the test set. During the training phase, the model was trained using waveform features. To mitigate the risk of overfitting, a validation set comprising 20% (222 images) of the training data was randomly selected. This validation set was used for fine-tuning hyperparameters and obtaining the optimal model. Finally, The model's capacity for prediction and generalization was evaluated using the test set.

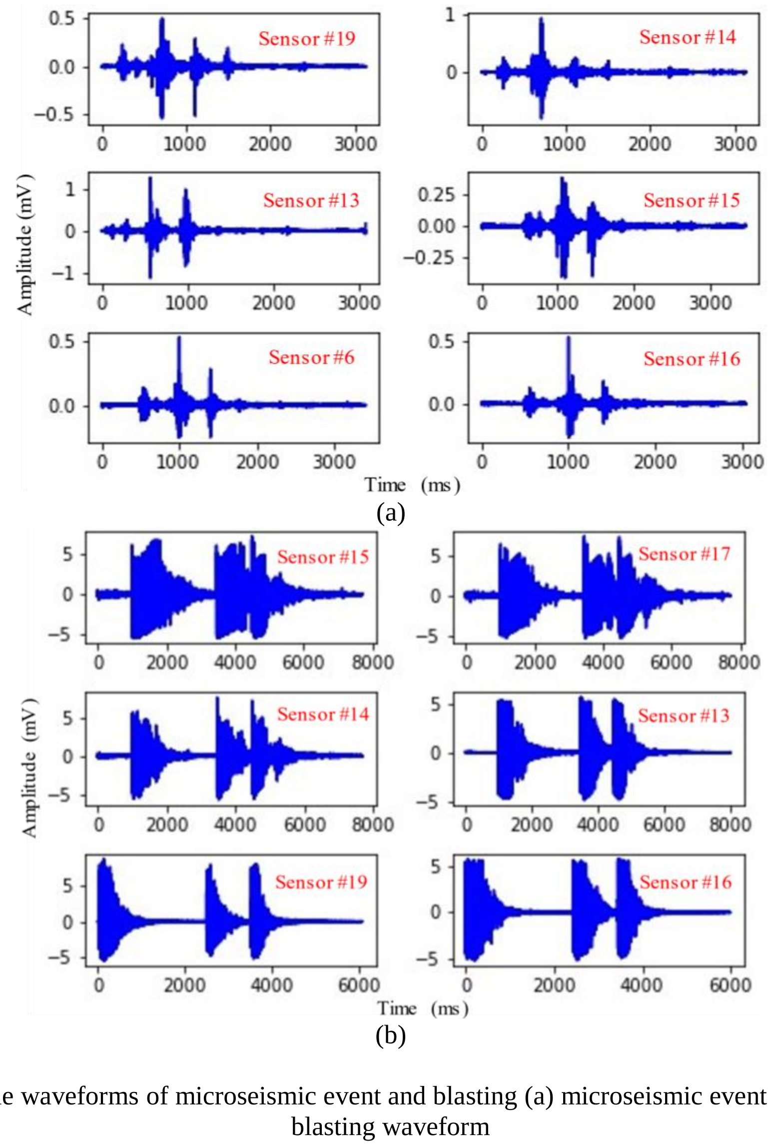

Figure 2. Example waveforms of microseismic event and blasting (a) microseismic event waveform and (b) blasting waveform

Table 2. Data sets and their divisions

Type	All	Training set (80%)	Testing set (20%)
Microseismic	512	410	102
Blast	874	699	175
Sum	1386	1109	277

3.2. Experiment

For the hyperparameter settings of CNN model training, different models had different initial learning rates, and the best parameter values need to be selected after several network training sessions. The following parameters were chosen for the MS-CNN model: i) pick stochastic gradient descent with momentum (SGDM) as your optimization function; ii) define the first learning rate as 0.001; iii) choose six epochs as the maximum number; iv) decide on 16 as the mini-batch size; v) select a 10-period validation frequency. Next, we examine the manner in which the MS-CNN model performed in terms of the training results and the test outcomes, respectively.

3.2.1. Training results and analysis

The loss and accuracy indicators are essential in assessing the progress of the learning process. During training, the loss typically decreases over time as the model learns to better fit the training data. To monitor the accuracy and loss changes during training, these values are often computed at regular intervals, such as after each epoch or after a certain number of training batches. The accuracy and loss curves can then be plotted over time to visualize how they change during training. In this study, a five-fold cross-validation was utilized during the training process, and the changes in loss and accuracy of the MS-CNN model during training and validation were depicted in Figure 3. The results show that accuracy increased continuously with training time and eventually stabilized at 1.0, while the loss gradually decreased and converged to approximately 0.0. The loss and accuracy values of the validation set were consistent with those of the training set. The accuracy of the validation set eventually stabilized at 98.6%, with a loss value of 0.05. These trends in loss and accuracy are in accordance with the changes expected during neural network training. The accuracy and loss metrics are frequently employed to monitor the model's performance during the MS-CNN training process and decide when to stop training.

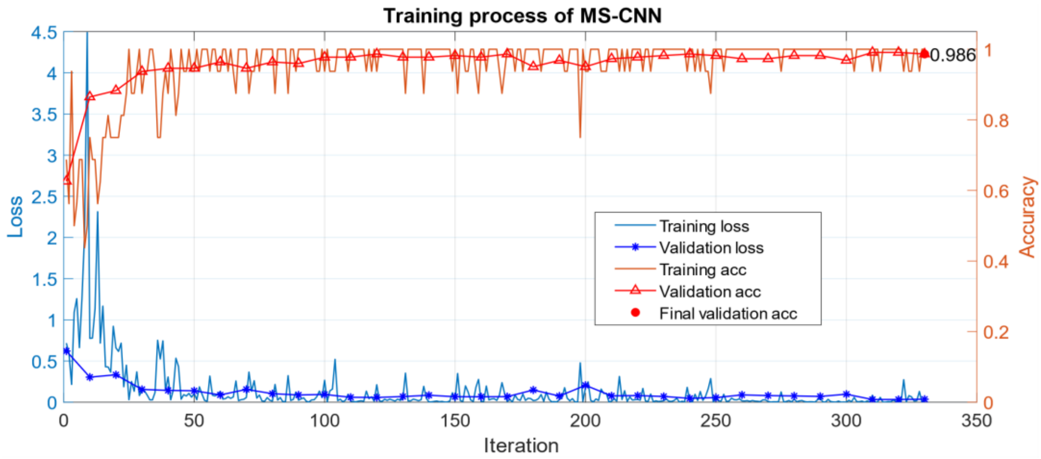

Figure 3. Accuracy and loss changes in MS-CNN training process

The accuracy of MS-CNN refers to the percentage of correctly classified samples in the training or validation set. As the model learns from the training data, the accuracy typically increases, although it may eventually plateau or even decrease if the model overfits the training data. The loss function employed in MS-CNN quantifies the disparity between the predicted labels and the actual labels for each input sample. During the training process, the objective is to minimize this loss function, thereby enhancing the model's capacity to generate precise predictions.

3.2.2. Test results and analysis

After the MS-CNN model training was completed, a new test dataset was used for prediction and classification, thus enabling analysis of the model performance. The identification results and time consumption of a CNN model can vary depending on the specific architecture, dataset, and hardware used to run the model. However, in general, the performance and time consumption of CNN models can be evaluated using the following metrics: The accuracy calculates the proportion of test set samples that were properly categorized. Better performance is indicated by higher accuracy. Precision counts the proportion of real positives among all correctly predicted positive outcomes. Less false positives are indicated by increased precision. The F1 score serves as a balanced metric, considering both precision and recall, and is calculated as

the harmonic mean of these two measures. To assess the classification prediction performance of the model, we employed five evaluation metrics: precision, recall, F1 score, accuracy, and testing time. The evaluation measures for single-category classification include precision, recall, and F1 score. The overall performance of the model is assessed using the accuracy metric and testing time.

As shown in Table 3, the MS-CNN model was very accurate in predicting microseismic events and blasts, with an overall recognition accuracy of 99.6%. In terms of the classification results of different events, those predicted as blast events were equal to the true category labels, with 100% precision. All microseismic events were successfully recalled, but one blast event was misjudged as a microseismic event, resulting in a 99% precision for microseismic events.

The receiver operating characteristic (ROC) curve is a visual representation that effectively illustrates the performance of a classification model. To generate the ROC curve, the model is first trained on a labeled dataset, and then the model's output probabilities are calculated for each input sample. After the probabilities are thresholded, binary predictions are created and compared to the true labels to calculate the true positive rate (TPR) and the false positive rate (FPR) at various thresholds. Plotting the TPR and FPR for different thresholds, as shown in Figure 4, allows us to construct the receiver operating characteristic (ROC) curve for the MS-CNN model.

The area under the ROC curve (AUC) is a measure of the model's overall performance, with a higher AUC indicating better performance. In the context of microseismic waveform recognition and classification, the ROC curve can be used to evaluate the performance of MS-CNN in distinguishing between different types of microseismic events or blasts. By analyzing the ROC curve, the optimal threshold can be selected to achieve a desired balance between sensitivity and specificity, depending on the specific application requirements. As shown in Figure 4, the MS-CNN model predicted microseismic events and blasts with high accuracy, reaching a value of 0.999 for the AUC, which was close to a perfect classifier.

Table 3. Testing results of MS-CNN

Type	Precision	Recall	F1 score	Accuracy	Testing time (s)
Microseismic events	0.990	1.000	0.990	0.996	0.310
Blasts	1.000	0.989	0.994		

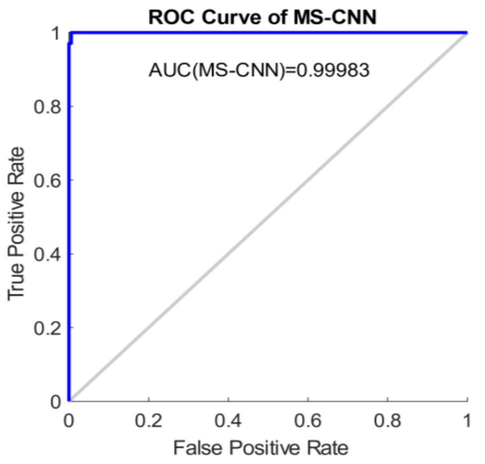

Figure 4. ROC curve of MS-CNN

4. DISCUSSION

Convolutional neural networks offer significant advantages over conventional techniques for the recognition and classification of multi-channel microseismic waveforms. One of the main advantages is the ability to extract more detailed information from the data using deep learning algorithms. This can result in more accurate classification of microseismic events, including the ability to distinguish between different types of events such as blasts, rock microfracture events, and noise. Another advantage is that using multi-channel microseismic waveforms helps to capture a more complete picture of microseismic activity, which can improve the accuracy of the classification process. In addition, as new data becomes available, CNN can update its parameters and improve its accuracy without requiring manual intervention.

One potential limitation of using CNNs for microseismic waveform recognition and classification is the need for a substantial volume of labeled training data. However, there are several techniques available to address this challenge, including transfer learning [39], data augmentation, and semi-supervised learning. Overall, the use of CNNs for microseismic waveform identification is a promising approach that has significant potential to enhance our understanding of rockburst activity and improve our ability to detect and respond to microseismic events. With the ongoing advancements in the field of deep learning, we can expect continuous enhancements in both the accuracy and efficiency of these models.

Using the same dataset, the existing CNN [1] model, AlexNet, GoogLeNet, and ResNet50 classic image classification models were first trained for modeling. Figure 5 shows the comparison results of the loss rate and accuracy of different CNN models during the training and validation process. Specifically, Figures 5(a) and 5(b) show the variation of loss rate and accuracy for the five models on the training set respectively. Figures 5(c) and 5(d) display the variation of loss rate and accuracy for the five models on the validation set respectively. The training and validation loss and accuracy trends of the five models were basically the same, and all of them were consistent with the variation of neural network training. Among them, the accuracy of the validation ranged from 97.75% to 98.65%, and the loss was basically in the range of 0.041-0.074. The CNN [1] model fluctuated the most in training and validation, while ResNet50 was the most stable and the best in validation. MS-CNN performed moderately in the training and validation process among these five models.

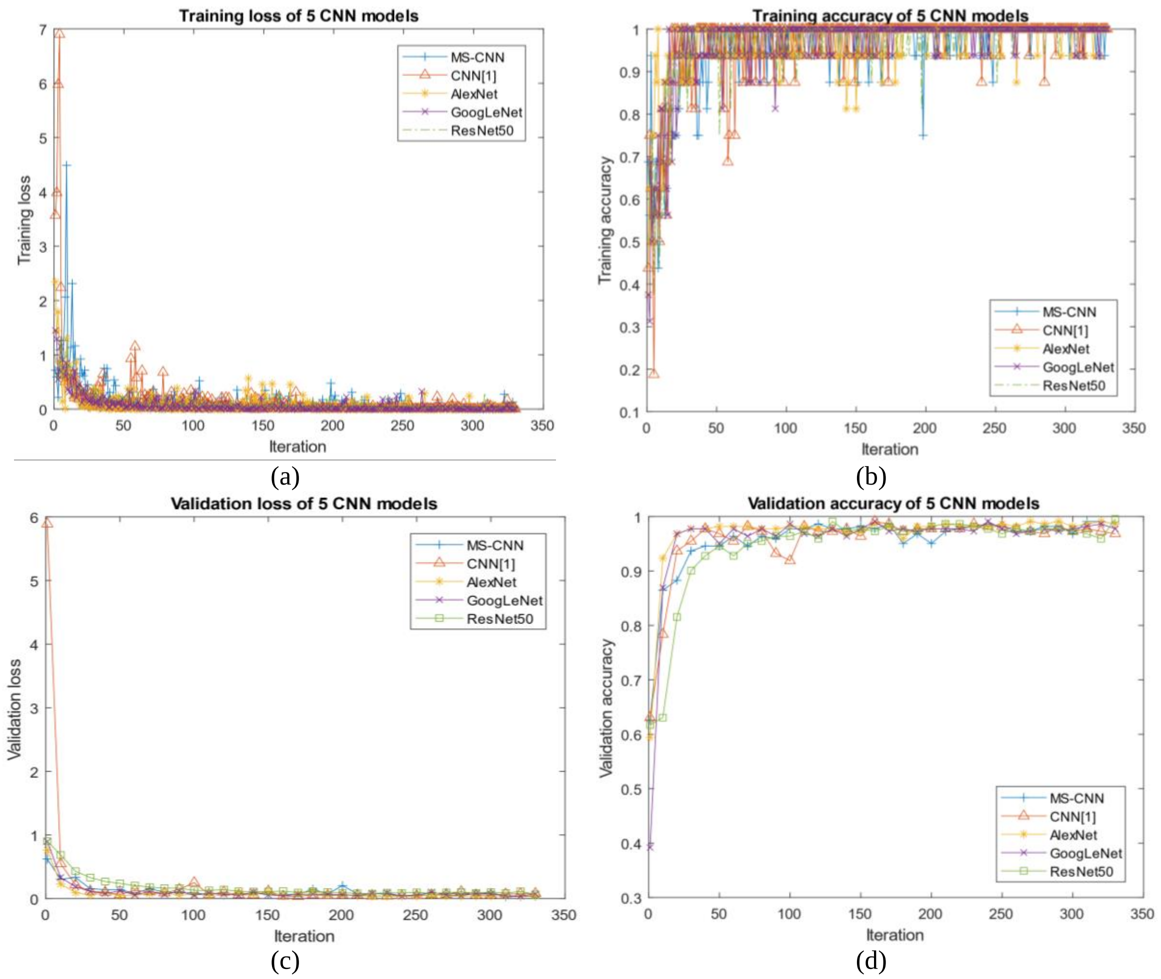

Figure 5. Training and validation results of five CNN models (a) training loss, (b) training accuracy, (c) validation loss, and (d) validation accuracy.

Based on the five selected evaluation metrics, the performance and effectiveness of the 5 CNN models can be assessed by comparing their time requirements and recognition results. The best model will be determined by the requirements of the particular application, such as accuracy, speed, and memory utilization.

For real-time applications, for instance, a model with high accuracy and little inference time can be favored, whereas a model requiring more memory and more training time might be chosen for applications where precision is crucial. Ultimately, the architecture, hyperparameters, dataset, and hardware employed will all depend on the identification results and processing time of CNN models, which must be assessed on a case-by-case basis shown in Figure 6.

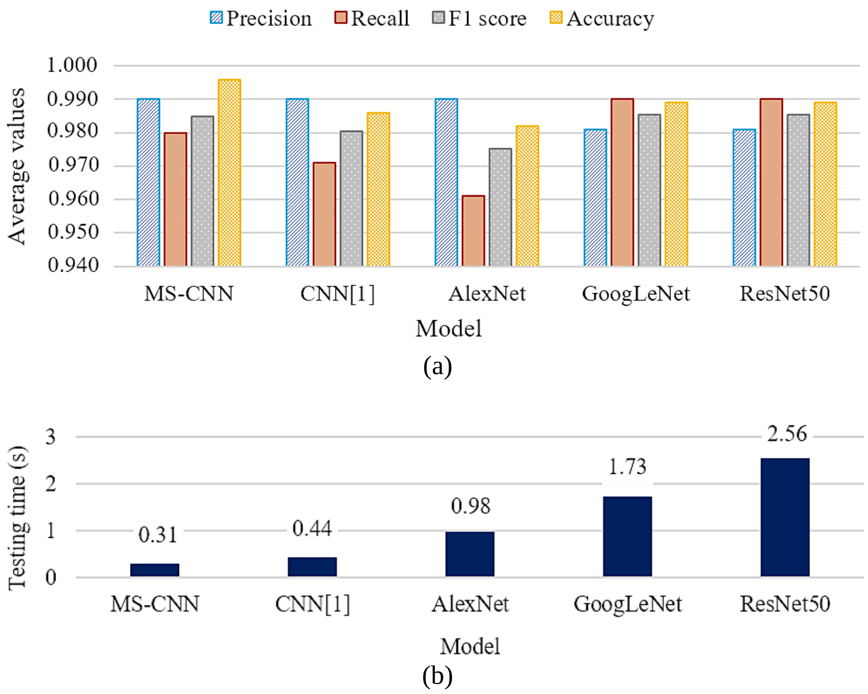

Figure 6. Identification results and time consumption for five CNN models (a) test results and (b) time consumption

Compared to the existing CNN model [1], we reduced the number of convolutional layers, modified the feature maps' parameters, and set the dropout value to 0.4. After multiple rounds of training and hyperparameter tuning, we obtained the optimal MS-CNN model. Experimental results indicate that MS-CNN is simpler and more efficient than the original CNN model [1] and transfer models such as AlexNet, GoogLeNet, and ResNet50 because it has fewer convolutional layers while maintaining good recognition accuracy on a limited dataset. From the comparative analysis of test results in Figure 6, it is clear that MS-CNN outperforms other models in terms of classification accuracy (99.6%) and recognition efficiency (which takes only 0.31 seconds to recognize 277 images in the test set) for the classification and recognition of microseismic events.

5. CONCLUSION

The recognition and classification of multi-channel microseismic waveforms using CNNs is a promising approach for accurately identifying microseismic signals. CNN-based models leverage the power of deep learning algorithms to effectively extract and analyze features from complex microseismic data, enabling accurate event classification based on waveform characteristics. The use of multi-channel data allows for a more comprehensive analysis of microseismic events, leading to improved classification accuracy and reduced false positives. Moreover, the adaptability of CNNs to new data makes them suitable for real-time applications, such as rockburst monitoring and early warning systems. Developing CNN-based models for microseismic waveform identification has significant potential to enhance our understanding of mining seismic activity and improve our ability to detect and respond to microseismic events. Advancements in deep learning will further increase the accuracy and efficiency of these models, making them increasingly valuable tools for rockburst analysis and prediction. This paper proposed the MS-CNN model, which demonstrated outstanding

performance in recognizing and classifying multichannel microseismic signal waveforms with high speed and accuracy. Compared to existing CNN models and classical image recognition and classification models, such as AlexNet, GoogLeNet, and ResNet50, the MS-CNN model achieved the best classification results with 99.6% accuracy and the shortest dataset identification time. Therefore, the MS-CNN method is practical for engineering applications where automatic recognition and classification of microseismic events and blasts are necessary.

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